# The Distribution of Economic Public Opinion in the American States<sup>\*</sup>

Matthew S. Levendusky Assistant Professor Department of Political Science University of Pennsylvania mleven@sas.upenn.edu

Jeremy C. Pope Assistant Professor Department of Political Science Research Fellow Center for the Study of Elections and Democracy Brigham Young University jpope@byu.edu

May 20, 2008

#### Abstract

How heterogeneous are the beliefs of citizens in a given state? Are citizens' views more diverse in some states than in others? While a number of methods exist for estimating the average liberalism of a state's population, there is no general method for estimating the heterogeneity of citizens' views. This paper provides a method to answer this question. In addition to providing this new measure, we make two additional contributions to the literature. First, we demonstrate that demographic variables are a poor proxy for opinion diversity, and actual opinion measures should be used whenever possible. Second, we illustrate how our measure problematizes much of the conventional wisdom about red and blue states. Together, our results show that the diversity of state opinion is both descriptively important and useful for solving a variety of substantive puzzles.

<sup>\*</sup>Paper prepared for presentation at the State Politics and Policy Meetings, Philadelphia, Pennsylvania, May 2008. We are grateful to Kevin Arceaux, Morris Fiorina, Jeff Grynaviski, Stephen Jessee, Frances Lee, Chris Karpowitz, Seth Masket, Lynn Vavreck, Stephen Voss, seminar participants at Brigham Young University, UCLA, the APSA 2007 meetings, and the MPSA 2008 meetings for helpful comments, and to Jamie Carson, James McDonald, and Christopher Palmer for sharing their data with us. Any remaining errors are our own.

How heterogeneous are voters' preferences within a given state? Are some states more ideologically homogeneous than others? While the literature provides numerous estimates of the average liberalism or conservatism of a given state (see, among others, Wright, Erikson, and McIver 1985; Berry et al. 1998; Brace et al. 2002), our ability to estimate the variation around this mean is much more rudimentary. Typically, scholars assume that demographic heterogeneity proxies for opinion heterogeneity (see, among others, Sullivan 1973; Aistrup 2004; Gronke 2000). But do more demographically diverse areas actually exhibit higher levels of opinion diversity? Resolving this measurement quandary is essential to further theoretical development in numerous areas of American politics. Take, for example, the study of Congress. The ideological diversity of a member's constituents affects her electoral fortunes (Fenno 1978; Fiorina 1974), roll-call voting (Lewis and Gerber 2004; Bailey and Brady 1998), and pattern of position-taking (Jones 2003). Without a valid measure of preference heterogeneity, none of these theoretical propositions—nor any related ones—can be accurately tested and evaluated.

This paper resolves this dispute in two steps. First, it develops a new measure of opinion diversity at the state level using national survey data. Second, it uses this new measure to reassess the relationship between demographic and opinion diversity. On this later point, our results are unambiguous: there is only a weak empirical relationship between demographic heterogeneity and opinion diversity. Demographic and opinion heterogeneity are distinct concepts, and they should not be treated as interchangeable. When testing theories about the effects of preference heterogeneity, scholars need measures of opinion diversity, not demographic diversity.

To demonstrate the utility of our method to applied scholars, we also reexamine the "red state/blue state" literature. Prior scholarship on this topic relies almost exclusively on difference of means tests to distinguish between red and blue states (Fiorina, Abrams, and Pope 2005; Abramowitz and Saunders 2005). We ask how the conclusions would change if we considered the entire distribution of opinion within the state rather than just the mean. Our

results show that states are much more heterogeneous that previous methods suggested, and the claims of stark differences between states cannot be sustained upon closer examination. But as we discuss in the conclusion, this is only one of many areas where our measure may be of use to scholars. We outline a variety of other topics—including elections, Congressional behavior, and policy-making—where our measure may help scholars to make substantive advances.

The paper proceeds as follows. We first discuss the previous approaches in the literature and discuss the need for our approach. We then detail our model, data, and our strategy for estimation and inference. We then go on to validate the results of our model using previous approaches, and then consider applications of our model. The paper concludes with a discussion of the findings and suggestions for future work.

### **Previous Approaches**

The study of the state-level ideology has a long history in political science, dating back to classic works by scholars such as Key (1949). While a variety of measurement techniques have been proposed in the literature, most scholars adopt the survey-based approach of Wright, Erikson, and McIver (1985), which uses national survey data to generate estimates of the average liberalism of each state. Other scholars have employed this same basic approach with a variety of different data sets to produce similar measures (Brace et al. 2002; Bartels 2005; Norrander 2001).<sup>1</sup>

These estimates are an important contribution to the literature, but they still do not address the question of heterogeneity. How heterogeneous is the distribution of ideology

<sup>&</sup>lt;sup>1</sup>There are also additional approaches to measuring state ideology not rooted in the tradition we discussed above (see, e.g., Park, Gelman, and Bafumi 2004; Berry et al. 1998; Weber 1971). These strategies are less related to our own and are typically not concerned with estimating preference heterogeneity, so we omit a discussion of them here in the interest of space.

within states? Are some states less homogeneous than others? The previous approaches estimate the mean of state opinion, but tell us almost nothing about the variation around that mean. States are generally large, both in terms of geography and population, and are consequently diverse places. Take California as an example. While towns like San Francisco and Berkeley are undoubtedly among the most liberal in the nation, other areas—like Orange and Imperial Counties—are quite conservative. The average Californian may be relatively liberal, but there is a large degree of variation across the state. Many other states have similar patterns of opinion diversity that are lost by focusing only on mean of the ideological distribution in each state.

Past efforts to measure opinion heterogeneity have relied upon demographic variables (Sullivan 1973; Bond 1983; Fiorina 1974). Bond, Covington, and Fleisher (1985) summarize the logic justifying this choice: "Although demographic characteristics of constituencies such as residency patterns, employment, income, race, etc. are not directly political, they may provide the basis for political cleavages at election time" (516). While undoubtedly demographics and opinion are related at some level, equating state or district opinion diversity with demographic diversity requires strong untested assumptions. Unless we can assume that on average states that are more demographically diverse have citizens with more diverse attitudes, we cannot be sure that demographic diversity translates into opinion diversity—the assumption made by previous scholars. Needless to say, if this assumption does not hold, then our estimates of the effects of heterogeneity may well lead us astray. By generating a direct measure of *opinion* diversity, we will be able to test the relationship between demographic diversity and opinion diversity.

As an alternative to demographic variables, some scholars use opinion data to estimate the ideological heterogeneity of voters within a state (e.g., by calculating the standard deviation of various opinion items, see Krasno 1994). While this is an improvement over demographic items, it too suffers from an important limitation: we cannot know the heterogeneity of constituents' opinions with certainty. While we may have indicators of constituent opinion, it

cannot be directly observed, and hence cannot be known definitively—our estimates of opinion heterogeneity are necessarily contaminated with some unknown amount of measurement error, and our models should account for that fact. This uncertainty becomes particularly consequential if our goal is to estimate the relationship between preference heterogeneity and some political outcome (e.g., election results) in light of the pernicious effects of measurement error on regression coefficients. A key advantage of our method is that our model allows us to account for the error in our measure in a systematic way, thereby correctly estimating the relationship between preference heterogeneity and other political outcomes (for more on this point, see Treier and Jackman 2008).

In order to overcome these limitations, we develop a new model of state-level ideology. Like previous approaches, we estimate the average level of liberalism in a given state, but we also estimate how ideologically homogeneous or heterogeneous a states' voters are. For the latter part of the model, we build on the work of Lewis (2001) and Lewis and Gerber (2004), who were among the first to address this problem (see also Jessee 2005). Our model expands on this work in two ways. First, this previous work used a unique but time-bound data set: the ballot image data from the 1992 elections in Los Angeles county. We instead consider the population writ large using survey data from recent national polls. Second, we expand the model to consider binary, continuous and ordinal indicators (the ballot image data is all binary data). As such, our model offers an important contribution to the literature in its own right.

### The Model

To learn about the distribution of ideology in a given state,<sup>2</sup> we first learn about the ideology of the citizens of a given state. That is, we build a model for the ideology of individuals, and aggregate to the state level, subject to some restrictions about the distribution

 $<sup>^{2}</sup>$ We define the term "state-level ideology" below, see the discussion on page 11.

of respondents within states.<sup>3</sup>

We begin the model with a simple proposition: each individual has a true unknown location on an underlying dimension. While we cannot observe that location directly (the scale is latent), we *do* observe multiple indicators of each individual's location on that underlying scale: each respondent places himself or herself on a variety of policy scales. These items—to varying degrees—reflect respondents' locations along this ideological continuum, and so will help us estimate where voters stand.

Practically—given ordinal survey items—we model individuals' responses to policy preference items as a function of these underlying dimensions using an ordinal item response model.<sup>4</sup> Here, let i = 1, 2, ..., N index individuals, and let j = 1, 2, ..., J index items, let  $k = 1, 2, ..., K_j$  index the ordinal response categories for item j. Then we can write out the model as:

$$Pr[y_{ij} = 1] = F(\tau_{j,1} - \alpha_j x_i)$$
$$Pr[y_{ij} = 2] = F(\tau_{j,2} - \alpha_j x_i) - F(\tau_{j,1} - \alpha_j x_i)$$
$$\vdots$$
$$Pr[y_{ij} = K_j] = 1 - F(\tau_{j,K_j-1} - \alpha_j x_i)$$

Here,  $y_{ij}$  is respondent *i*'s response to item *j*,  $x_i$  is respondent *i*'s location on the latent dimension (their latent issue preference),  $\alpha_j$  is a discrimination parameter telling us how much responses to item *j* distinguish between more and less liberal respondents on the latent dimension and  $F(\cdot)$  is the cumulative distribution function for the logistic distribution. The  $\tau_j$  parameters are a set of thresholds for each items just as in a standard ordinal model. Because the thresholds must be ordered (i.e.,  $\tau_{j,k} > \tau_{j,k-1}$ ), we parameterize the thresholds

<sup>&</sup>lt;sup>3</sup>Although we focus on states here, we wish to stress that our model could be used at any level of geographic aggregation (e.g., counties, Congressional districts, etc.).

<sup>&</sup>lt;sup>4</sup>The model of voter issue positions is very similar to the ones developed in Treier and Hillygus (2006); Treier and Jackman (2002). Jacoby (1990) also presents a similar model of voter issue positions using Guttman scaling.

as  $\tau_{j,k} = \sum_{l=1}^{k} \delta_{j,l}$ , and for  $l \ge 2$ ,  $\delta_{j,l}$  must be greater than 0. The restriction on the  $\delta$  terms ensures that they are ordered properly.<sup>5</sup>

In addition to these ordinal items, we also use two additional types of data: data from binary (yes/no) items and continuous items. For the binary items, we can write out the model as:  $P(z_{ij} = 1) = F(\beta_j x_i - \zeta_j)$ , where  $z_{ij}$  is respondent *i*'s response to item *j*,  $x_i$  is voter *i*'s location on the latent trait (as before),  $F(\cdot)$  is again the cumulative distribution function for the logistic distribution, and  $\zeta_j$  and  $\beta_j$ , are the item difficulty and item discrimination parameters (respectively) for item *j*; see Clinton, Jackman, and Rivers (2004) for more information on the standard binary item setup.

For continuous items, the model can be written as:  $c_{ij} \sim N(\lambda_1 + \lambda_2 x_i, \omega_j^2)$ , where  $c_{ij}$  is respondent *i*'s response to item *j*,  $\lambda_1$  and  $\lambda_2$  are again difficulty and discrimination parameters,  $x_i$  is again the respondent *i*'s location on the latent trait, and  $\omega_j^2$  is an unknown variance to be estimated. Again, see Jackman (2004) for more on this type of setup, especially on combining multiple types of data in a single measurement model.

To study how the distribution of opinion varies by state, we need to make an assumptions about said distribution. Again, assume that voters are indexed by i = 1, 2, ..., N, arranged in states m = 1, 2, ..., M. Then:

$$x_i \sim N(\mu_{m[i]}, \sigma_{m[i]}^2)$$

Where m[i] indicates that voter *i* resides in state *m*. We assume that voters in each state are distributed normally;  $\mu_m$  tells us where the "average" (mean) voter is located in state  $m, \sigma_m^2$  measures the within-state variation in the distribution of opinion in state *m*. These parameters are of central interest to us:  $\mu$  contains information on how liberal or conservative the average citizen in a given state is, and  $\sigma$  tells us how widely dispersed the voters in a particular state are: are they all ideologically similar, or is there relatively more variation in their beliefs?

<sup>&</sup>lt;sup>5</sup>For more on the standard item response model setup, see Johnson and Albert (1999).

Here, we assume voters are normally distributed as a convenient starting point. While this does impose some restrictions on the shape of the voter distribution (e.g., it rules out bimodal distributions), this choice is, in our view, justified. The alternative would be to adopt a more complicated functional form, either by using another type of distribution or by using a mixture model (Lewis 2001; Lewis and Gerber 2004; Jessee 2005). While such models are possible, they are notoriously plagued by estimation problems and themselves require a host of restrictive assumptions, making them far from an ideal choice. It is not obvious that the substantial increase in complexity (as well as additional strain on the data) yield an appropriate substantive payoff here; this is a topic we leave for future research.<sup>6</sup>

The model we outlined above is relatively complicated, with parameters for each voter, item, and state in the analysis, complicating traditional modes of inference. Happily, Bayesian techniques for estimation and inference are well-suited to this type of problem (Clinton, Jackman, and Rivers 2004), so we adopt them here. We provide the technical details of our approach in the accompanying reviewer's appendix, we refer the interested reader there for the details.

Absent additional restrictions, the model as presented above is not identified owing to the fact that state ideology has no natural metric. Rivers (2003) verifies that two restrictions are needed to identify a unidimensional model—typically one definition to set the location and one to set the scale. We fix the mean of the distribution for one state (here, Ohio) to be 0 (that is,  $\mu_{\text{Ohio}} = 0$ ). We normalize Ohio because the raw data indicates it is a relatively moderate state, thereby making our scale easier to interpret. We could, however, have chosen any other state for this restriction without altering the substantive content of our measure. To define the scale of the metric we constrain the discrimination parameter on the minimum wage item to be 1.<sup>7</sup> With these restrictions in place, the latent trait is

<sup>7</sup>Readers should not attach any substantive significance to these choices, they are simply

<sup>&</sup>lt;sup>6</sup>We perform some basic analysis of the appropriateness of the assumption of normality, see the reviewer's appendix for the details. The results do not suggest that a more complicated model is warranted.

identified and we can proceed with our analysis.

### Data on Ideology

The primary data for this project came from the common content module of the Cooperative Congressional Election Study, better known as the CCES (Ansolabehere 2006).<sup>8</sup> The data from this survey is not a random sample of the U.S. population (as would result from, say, a standard random-digit-dialing (RDD) telephone survey), but instead comes from the internet panel of the Polimetrix Corporation. In order to generate data reflective of the U.S. population (rather than just their online panel), Polimetrix uses a proprietary matching algorithm that matches CCES respondents to respondents from the American Community Study (ACS), a high-quality random sample of population conducted by the U.S. Census Bureau (see Rivers 2007 for the details of this procedure). The end result is that while the CCES sample is not a genuine random sample of the U.S. population, it should closely match the demographic makeup of the population as measured by the ACS.

Data quality becomes an obvious concern when using a non-probability sample (Malhotra and Krosnick 2007). This is perhaps particularly true given the relative novelty of the Polimetrix sample matching procedure. Several recent studies, however, suggest that the CCES data closely parallels other types of survey data. Hill et al. (2007) argue that the CCES sample resembles standard RDD surveys, although the volunteer sample is unusually well informed about politics (relative to a general population sample). Jacobson (2007) reaches a similar conclusion, demonstrating that the CCES data very closely matches other polling data collected in 2006. Vavreck and Rivers (2007) verify that the CCES data have more accurate election predictions (in terms of root mean squared error, which accounts for identifying restrictions: the issue is akin to measuring temperature using the Fahrenheit or the Celsius scale (Jackman 2004). Different restrictions yield different scales, but the underlying quantity of interest is the same.

<sup>8</sup>For more information on the CCES, see http://web.mit.edu/polisci/portl/cces/ index.html. both sampling variability and bias) than other phone and internet polls in the field in 2006. While there is certainly more work to be done in this area to elucidate the strengths and weaknesses of this type of data, these results are encouraging. While we do not think the CCES data are perfect, or even ideal, our study would not be feasible without this sort of large sample of every state in the nation. Given this, we acknowledge the limitations of the CCES data, but accept them as necessary evils, at least in the short term.<sup>9</sup>

To actually measure ideology, we selected items that assess political preferences along the left-right economic divide. This is the long-standing division in American politics that separates respondents based on how much they would like to see the government intervene in the economy, with those on the left favoring more intervention than those on the right (Shafer and Claggett 1995). While economic issues are not the only ones relevant to policymaking, we leave the complicated question of preferences along other dimensions for future work. Specifically, the items we use in the CCES to measure respondents' preferences are: (1) whether or not social security funds should be invested in the stock market, (2) whether we should protect the environment even at the expense of losing jobs, (3) whether the state government should increase taxes or cut spending, (4) whether to balance the federal budget our first step should be to cut domestic spending, (5) the respondent's liberal-conservative self-identification, and (6-7) and how the respondent would have voted on two roll-call votes: whether or not we should cut capital gains taxes and whether or not we should increase the federal minimum wage. Dimensional analysis of the data strongly suggest that a onedimensional fit is appropriate for these items: an eigenvalue decomposition of the correlation matrix of the items yields a first eigenvalue of 4, with a second eigenvalue of 0.6. Given this, we proceed with a unidimensional model.

Even with the large national sample size of the CCES, we had to restrict our attention to <sup>9</sup>We have also used our method to generate estimates for the 1988-1992 Senate Election

Study conducted by the National Election Study and the 2000 Annenberg National Election Study, see the appendix for more details.

a subset of states. In particular, we found that we could only meaningfully compute both the mean and the variance of the state-level ideology distribution for those states with more than 200 respondents. This restriction means we lack information on 11 states: Alaska, Delaware, Hawaii, Montana, North Dakota, Nebraska, New Hampshire, Rhode Island, South Dakota, Vermont, and Wyoming. For the remainder of the paper, we focus our attention on the 39 remaining states where we feel we can draw more confident inferences about ideology.

Before proceeding to the results we wish to offer two notes on the substantive content of our measure. Typically, scholars distinguish between two different conceptions of ideology: symbolic ideology, which captures individual's conception of themselves as a liberal or a conservative, and operational ideology, which measures individual's policy preferences about what government should actually do (Stimson 2004). Given the indicators we use in this paper, our measure is most appropriately classified as state-level operational ideology, often termed "policy mood" in the literature (Erikson, MacKuen, and Stimson 2002; Stimson 1999). In that sense, while our model builds on past work in the tradition started by Wright, Erikson, and McIver (1985), it captures a slightly different dimension than most of the scholarship in that tradition (which typically measures state-level symbolic ideology). Both measures are important theoretically and empirically for the study of politics, and we stress that researchers interested in a substantive problem should select the measure more closely matching their theory (for an excellent discussion of the issue involved in the operational vs. symbolic ideology debate, see the discussion surrounding Berry et al. 2007). That said, for scholars who want state-level estimates of operational ideology/policy mood, our measure makes an important contribution to the literature.

Second, while we call our measure "state-level ideology" to be consistent with past scholarship, what we have is best thought of as an *indicator* of ideology. Ideology is a notoriously complex concept, encapsulating not only policy preferences, but also consistency across issues, and connections to abstract conceptions like "liberalism" or "conservatism" (Gerring 1997). So while we use the term "state-level ideology" throughout the paper, we stress that there is some slippage between out empirical measure and theoretical concept of ideology.

### **Results: State Mean and Variance Parameters**

Before turning to the model results, a brief word on our measure's validity is in order. To assess model validity, we examine the relationship between our estimate of the ideological location of the average voter in a state and various indicators of state partisanship and ideology: the average response in each state to the liberal-conservative self-ID question (note that this is the method used by Wright, Erikson, and McIver to generate their estimates of state ideology), the average partisanship in the state, and the share of the (two-party) Presidential vote going to the Democratic nominee in the state in 2004. The correlation with the average liberal-conservative self-placement is 0.94. We also found a strong relationship between our measure and the 2004 election returns (a correlation of 0.79) and between our measure and self-identified average partisanship (also a correlation of 0.79). These strong and sensible correlations suggest that our measure captures an important dimension of voter preferences. With this in mind, we can turn to the model results more confident that we've captured an important dimension to American public opinion. <sup>10</sup>

Which states are (on average) the most conservative? The most liberal? In figure 1, we give the posterior means and 95% highest posterior density intervals<sup>11</sup> for the state mean parameter ( $\mu_m$ , where *m* indexes states).

#### [Figure 1 about here.]

As figure 1 reveals, there is both a considerable amount of heterogeneity and homogeneity among the states. Heterogeneity in that various states are more or less conservative:

<sup>10</sup>In the reviewer's supplemental appendix, we present an additional validity check by plotting our measure against the raw data. These plots again strongly suggest a high degree of validity for our approach.

<sup>11</sup>Highest posterior density intervals (HPD intervals) are the Bayesian analog to frequentist confidence intervals.

some states are quite liberal (OR, NY, MA—largely states on the Pacific coast and in New England), others more moderate (PA, FL, NJ) and others more conservative (UT, AL, ID–largely states from the Mountain West or the deep South). Based on our model, we would estimate Oregon, New York, or Massachusetts to be the most liberal state in the union (probability of 0.55, 0.19, and 0.17, respectively). Likewise, we estimate Alabama, Idaho, or Mississippi to be the most conservative state in the nation (probability 0.42, 0.27, and 0.15, respectively). All of this largely conforms to the conventional wisdom about the geographic distribution of ideology in the US—the more liberal areas are clustered on the coasts and the more conservative spots are in the interior.

There are a few states that might seem a bit out of place. For example, our results indicate that New Mexico is estimated to be the 4th most liberal state. We wish to stress, however, that this is a function of the data and not our method. Even if we just took simple averages of the raw CCES data, we would estimate NM to be the 4th most liberal state, and using only the average self-placement item, it would be the 6th most liberal state. In other words, the *data* on New Mexico indicate it is particularly liberal, not our scaling method. There are two possibilities. It is possible that New Mexicans are not really that liberal, but rather the CCES sample may not reflect the true distribution of opinion in New Mexico (particularly given the small sample of only 321 respondents). Alternatively, New Mexico's reputation for moderation may have more to do with a relatively socially conservative environment (a dimension not captured in the questions we selected). We leave exploring these possibilities for future research, simply noting here that these types of discrepancies are a function of the data, not the model.

Figure 1 highlights an important advantage of our method over many previous approaches our model allows us to calculate the uncertainty in our estimates of the average ideology within each state. For example, looking at figure 1, we see a few clusters of states: a cluster of states that we can confidently (that is, with probability greater than 95%) conclude are more liberal than Ohio (recall that we fixed the position of the typical voter in Ohio to 0 for purposes of model identification), a group we cannot really distinguish from Ohio, and a group more conservative than Ohio.<sup>12</sup> In other words, once we take measurement error into account, states are less easily differentiated along this dimension than we might initially suspect.

To reinforce this point, we can compare the ideology of various states and ask how confident we can be that one state is more liberal than another. We consider three comparisons: Oregon vs. Washington (two liberal states), Louisiana vs. Alabama (two conservative states), and New Jersey and Pennsylvania (two moderate states). When comparing liberal or conservative states in the tails of the ideological distribution, we can usually make relatively fine distinctions: the probability that Oregon is more liberal than Washington is 0.96, and the probability that Alabama is more conservative than Louisiana is 0.90. But near the center of the distribution, making these sorts of distinctions becomes more difficult: the probability that New Jersey is more liberal than Pennsylvania is 0.66, which falls far short of conventional levels of statistical significance. Once we take seriously the proposition that state ideology is not known with certainty, differentiating states becomes quite difficult.

This point has profound substantive consequences. It may seem simple to suggest that we have a limited ability to draw definitive conclusions about the relative ideology of states. It is anything but. Even in 2006—by many accounts a highly polarized age—ordinary Americans remain more heterogeneous at the state level than has generally been appreciated. That is, even states that one is tempted to think of as liberal or conservative bastions—say California or Texas—are in fact quite diverse. California has a number of conservative regions in the inland farming communities, and Texas has more liberal enclaves in Austin and other large cities like Houston. There are real limits to our ability to distinguish between the average

<sup>&</sup>lt;sup>12</sup>Throughout the paper, when we say "state X is more liberal (conservative) than state Y," the reader should take this to mean "the mean of the voter distribution in state X is estimated to be more liberal (conservative) than the mean of the corresponding voter distribution for state Y." We adopt this rhetorical convention for simplicity.

voter in different states.<sup>13</sup>

But beyond the mean, there is also the issue of the standard deviation within each state: how ideologically homogeneous or heterogeneous are voters within a given state? Figure 2 plots the within-state standard deviation parameters (both posterior means and 95% HPD intervals).

#### [Figure 2 about here.]

As figure 2 reveals, there is real variation in how ideologically diverse voters are within a given state. Interestingly, many of the most ideologically diverse states do not necessarily have the largest populations. Many moderately sized states—for example, Colorado, Arizona, Minnesota, and Oregon—have a diverse distribution of opinions. Colorado has liberal enclaves in Denver and Boulder, but also more conservative regions around Colorado Springs and the large rural sections of the state. Oregon has liberal communities like Eugene and Portland, but more conservative residents in the eastern farming communities. While in general larger states are more diverse, the standard deviation of opinion is more than just a proxy for population size.

But there is an important limitation to this discussion as well. Note that even more so here than in the case of the state mean parameters, there is a real limitation on our ability to confidently distinguish more or less ideologically heterogeneous states. We can

<sup>13</sup>There is one small caveat to this discussion, however. As with all statistical procedures, our model is more accurate with larger samples. As an illustration of this point, in the reviewer's supplemental appendix, we plot the uncertainty in our estimate of the posterior mean against the sample size, and demonstrate that there is a strong relationship. So the standard error of the mean is smaller in CA (with more than 3000 respondents) than it is in Idaho (with only 247 respondents). So if we had enormous sample sizes in every state, we would be able to make somewhat finer-grained distinctions between states. But looking at the results, small sample size isn't the main limitation: its simply that most states are fairly similar places ideologically.

make relatively fine distinctions in the tails—the probability that Texas is more ideologically homogeneous than California is 0.94—making these sorts of distinctions in the middle of the distribution is more difficult. The probability that Illinois is more heterogeneous than Indiana is only 0.60. Making distinctions that meet or exceed traditional standards of statistical significance will be quite difficult in many cases given these sorts of samplesizes. Even with more than 30,000 observations in the CCES, we are running up against the limitations of our data. Put slightly differently, to more confidently assess differences in ideological heterogeneity between states, we would need either more data or more restrictive assumptions.

### **Results:** Opinion and Demographics

Although we find considerable similarity between states, we *do* find important differences as well. To what extent are these differences in opinion across districts a result of different demographic characteristics? This question is particularly important given that scholars have traditionally relied on demographic variables as proxies for state opinion variables (Weber 1971; Fiorina 1974; Bullock and Brady 1983; Bond, Covington, and Fleisher 1985; Sullivan 1973). Does demographic diversity actually translate into opinion diversity?

Here, we examine how well demographics proxy for both the mean and the variance of state opinion. Table 1 gives the relationship between several important demographic characteristics and our measure of the mean and variance of state opinion (details on the demographic measures used are provided in the supplemental appendix).

#### [Table 1 about here.]

The most striking feature of table 1 is the relatively weak relationship between most demographic aggregates and both the mean and the variance of state-level opinion. For the mean level of opinion, only a handful of items reach conventional levels of statistical significance: states that have a higher percentage of the workforce in a labor union are more liberal and the effects of home ownership and median income are borderline statistically significant. Note that other factors one might expect to play a difference—percent African-American, percent urban, population density, etc.—have no statistically discernible effect on the mean level of ideology in a given state.

For the variance parameters, we see a similar pattern of null results. The only statistically significant predictor of state ideological heterogeneity is population size, with states with larger populations between more heterogeneous. It would be incorrect to conclude, however, that the two are analogous concepts: the correlation between the two measures is only 0.27, and a number of moderately sized states are quite heterogeneous by our measure. Population size is definitely *not* the only determinant of state ideological heterogeneity.

But how does our measure of opinion heterogeneity relate to the most prominent measure of diversity in the literature, the Sullivan index (Sullivan 1973)? Sullivan constructed a diversity index for the states based on six variables: education, income, occupation, housing ownership, foreign-born, and religion. The resulting index "is nicely interpretable in probability terms, since it represents the proportion of characteristics upon which a randomly selected pair of individuals will differ" (Sullivan 1973, 70). This measure provides a straightforward way to assess the demographic diversity of a state and has been widely used in the applied literature (see, e.g., Fiorina 1974; Bond 1983; Bond, Covington, and Fleisher 1985; Aistrup 2004).

Looking at the results in column 2 of table 1, the answer is clear: while there is some relationship, demographic indices are not good proxies for opinion diversity. The Sullivan Index is modestly related to our measure of opinion diversity: the two are correlated at 0.31, but the coefficient is not statistically significant (p=0.27). The problem with the Sullivan index as a measure of constituent diversity is that demographics do not neatly translate into opinions on key political issues, at least at this level of aggregation. Our results make it clear that where actual opinion diversity measures are available, those should be substituted. Political science theories are written in terms of constituents' attitudinal diversity, not their

demographic diversity, and our measures should reflect that fact.<sup>14</sup>

Overall, the most important lesson here seems to be that we simply don't have a good sense of what demographic variables are related to either the mean or the variance of state opinion. Very few demographic variables are even weakly related to state liberalism or state opinion heterogeneity, even when those same variables have a strong individual-level relationship with ideology. Our results suggest that factors beyond state-level demographics drive variation in state ideology. These results, along with the earlier findings in the literature (Lewis and Gerber 2004; Kuklinski 1977; Erikson, Wright, and McIver 1994), should make it clear that demographics are *not* good proxies for opinion diversity at the state level.

# Application: Red States and Blue States

To demonstrate the utility of our measure to applied researchers, we use our measure to re-examine an area of considerable debate in the literature—the divergence between the ideological views of citizens in "red" (Republican) and "blue" (Democratic) states. Since the 2000 election, there has been an explosion of popular and academic interest in political polarization. In particular, a great deal of work focused on the "red-state/blue-state" comparisons, which all seemed to show a large gulf between voters in Democratic and Republican states. *Contra* much of the prior journalistic and impressionistic work, Fiorina, Abrams, and Pope (2005) showed that too much had been made of the red/blue divide: voters in both kinds of states hold fairly similar opinions. This conclusion has been challenged, however, in recent work by Abramowitz and Saunders, who argue that Fiorina and his co-authors have systematically understated the differences between red and blue states (Abramowitz and Saunders 2005, 2008). Here, we re-examine this debate and consider the role of hetero-

<sup>&</sup>lt;sup>14</sup>Of course, there are some circumstances where demographic diversity *is* the theoretical quantity of interest—for example, Adler and Lapinski's 1997 study linking constituents' characteristics to members' choices of committee assignments. Our caution is simply against scholars regarding demographic diversity as a substitute for opinion heterogeneity.

geneity. How would our conclusions about red and blue states change if we considered the entire distribution of opinion within each state, rather than just the mean?

Here, for simplicity, we compare two sets of states. First, we consider a relatively extreme pair of states: New York and Utah. Both states are estimated by our model to be relatively extreme ideologically, and both are lop-sided partisan states (e.g., New York is a "safe" state for Democrats at the Presidential level, likewise Utah is safe for Republicans at the Presidential level). Second, we consider states that are more moderate: New Jersey and Florida. These are states that we estimate to be much closer to the center of the ideological distribution and are more competitive at the Presidential level: in 2004, Kerry carried New Jersey with 53% of the two-party vote, Bush carried Florida with 52% of the vote. We chose these states as convenient exemplars of their categories (moderate and extreme states), but other states would give similar results. Here, we consider the benefit of our more complicated approach relative to the simpler difference of medians comparisons typically made in the literature. Figure 3 plots the implied distribution of voters in each state using the estimated model parameters discussed above.

#### [Figure 3 about here.]

As figure 3 shows, in both cases—even with the more extreme states—there is considerable overlap between the distributions.<sup>15</sup> Take New York and Utah. As one might suspect, we are virtually certain that the average voter in New York is to the left of the average voter in Utah (our model assigns this event a probability of approximately 1). However, when we look at the entire distribution of opinion, a different picture emerges. For example, suppose we drew a voter at random from each of the two states and compared their relative ideologies. What is the probability that the voter selected from Utah would be more conservative?

<sup>&</sup>lt;sup>15</sup>While the specific shape of the distributions is in part a consequence of our modeling procedure, the overlap between the distributions is not. If we used the raw data in lieu of our model estimates, the qualitative story would not change.

Here, the answer is only 63%, reflecting the large degree of overlap between the two distributions. Indeed, just about one-third of the New York voter distribution is estimated to be more conservative than the average voter in Utah. After taking the heterogeneity within each state into account, states seem more similar than different. Even if we can very clearly distinguish the "average" voters in each state, the overall distribution implies a much larger degree of heterogeneity than previously acknowledged.

This pattern of commonality emerges even more strongly when we examine the New Jersey/Florida comparison—both are ideologically moderate and competitive at the Presidential level. It is clear in figure 3 that the distribution of opinion in Florida and New Jersey is nearly identical, and we cannot assert with any real confidence that one state is more conservative than the other. Both comparisons (New York vs. Utah and New Jersey vs. Florida) point to the same conclusion: red and blue states have far more in common that the previous literature has suggested.<sup>16</sup>

There is an important caveat to keep in mind, however. We can find so much ideological common ground between red and blue states because states are large, heterogeneous, diverse places. Smaller geographic locales (e.g., counties or towns) will undoubtedly display more homogeneity: there's much less overlap between (say) lower Manhattan and Rich County, Utah (the latter recorded almost 90% of its votes for Bush in 2004). The point remains, however, that most states are not such uniform locales and diversity, rather than homogeneity, is the most striking feature of state public opinion. Most states in the union are at least somewhat ideologically heterogeneous.<sup>17</sup>

<sup>17</sup>There is an additional complication we have ignored here in the interest of simplicity. The analysis conducted above uses the posterior means of the state mean/standard deviation parameters. If, however, we were to include the measurement error in these parameters into our estimates, we would have even less ability, generally speaking, to distinguish the voter distributions. Here, we opt for the simpler choice since it adequately makes the point, but

<sup>&</sup>lt;sup>16</sup>Using the 2000 Annenberg data, we would reach similar conclusions, see the reviewer's supplemental appendix for more details.

Further, our analysis here looks only at economic issues focusing on how much the government should intervene in the economy. The patterns of results might look quite different if we focused on social issues like abortion and gay marriage. We leave this as an area for future research, but we simply note two points. First, as Fiorina, Abrams, and Pope (2005) note, even on these hot-button social issues, most Americans seek a middle ground. Second, even if the pattern on social issues were completely different and showed total separation between red and blue states, the fact that we show these patterns on economic issues is significant in and of itself: on these issues where difference of means tests show considerable differentiation, we should a great deal of similarity, an important finding in its own right.

# Conclusion

This paper outlined a new approach to measuring both the mean and the variance of state-level opinion on economic issues. Although the descriptive findings on the mean and variance of state opinion are important in their own right, we also made two additional contributions to the literature. First, we explored the relationship between our measures and demographics in light of the long tradition of using demographic variables as proxies for state-level opinion. We found demographic variables wanting as proxies for public opinion measures, and our results are clear: where available, real opinion measures should be used, particularly for measures of opinion heterogeneity.

Second, we showed how our measure can be employed to resolve substantive disputes in American politics. Specifically, we reconsidered the "red state/blue state" debate, and showed that once you move beyond a simple difference of means test, states are far more diverse and heterogeneous places than the extant literature has appreciated.

We wish to acknowledge a limitation of our work, however. We think our measure of note in passing that accounting for measurement error would generally mean *less* ability to differentiate states.

ideological heterogeneity holds tremendous promise and offers many exciting new opportunities for scholars. However, it is not the only way of thinking about ideological diversity, and in some situations, other approaches may prove more fruitful. Some scholars may prefer a measure grounded in the dimensionality of citizens' preferences (Ensley, Tofias, and de Marchi 2007), while others might prefer to think in terms of sub-constituencies (Bishin 2007). These other approaches provide a complement when scholars feel our measure is an inappropriate choice.

That caveat aside, we think our measure holds tremendous promise for a variety of substantive works. First, there is only limited prior work on how heterogeneity affects representation and a member's behavior in office. For example, does the ideological heterogeneity or homogeneity of a state affect roll-call voting (Lewis and Gerber 2004; Bailey and Brady 1998)? Does it affect what issues a member emphasizes to constituents (Fenno 1978)? Does it change the issues he or she works on in office? Do Senators from more diverse states tend to obfuscate their positions more frequently (Jones 2003)? Much more remains to be done on these topics, and our measure will help scholars address these important questions.

Second, our measure can be used to reassess the large literature on diversity and elections. Many scholars argue that members from more ideologically diverse districts will, all else equal, have lower re-election margins, stemming from the fact that challengers will be more easily able to construct a winning coalition in a diverse district (Fenno 1978; Fiorina 1974; Sullivan 1973). In the appendix, we consider one specific example of this diversity-elections linkage. While our analysis on this point is not definitive, it does suggest a link between opinion diversity and electoral outcomes, and (more importantly) it gives scholars the tools needed to address this question in future work.

Finally, more remains to be done on linking the diversity of constituent views and public policy outputs. Does heterogeneity impact policy outputs? Does it make it harder to achieve consensus on what needs to be done? Does this impact the types of interest groups active in state politics (Gray and Lowery 1993) or other aspects of state policy-making?<sup>18</sup> These are just some of the questions that our measure will help scholars to answer.

<sup>&</sup>lt;sup>18</sup>Although we do not explore this question here, Klingman and Lammers (1984) argue that there is a linkage between policy liberalism and state diversity.

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Posterior Mean, State Mean Parameter

Figure 1: Posterior means and 95% highest posterior density intervals for the state mean parameters.



# **State Standard Deviations**

Posterior Mean, State Standard Deviation

Figure 2: Posterior means and 95% highest posterior density intervals for the state standard deviation parameters.



Figure 3: The distribution of voters implied by the state-level mean and standard deviation parameters in two groups of states: the "extreme" states of New York and Utah on the left, the more "moderate" states of New Jersey and Florida on the right. In both cases, the state carried by the Democrat is the blue dashed line (New York and New Jersey), the state carried by the Republican is the solid red line (Utah and Florida). The most noteworthy feature of the graph is the degree of overlap between the states in each panel.

	Mean Opinion	Standard Deviation
Intercept	-11.18	1.68
	(8.89)	(6.37)
Percent African American	0.02	-0.08
	(0.05)	(0.05)
South	-0.60	0.31
	(0.53)	(0.49)
Percent Foreign Born	0.02	-0.07
	(0.06)	(0.06)
Percent Urban	0.004	-0.24
	(0.31)	(0.34)
Population Density	-0.02	-0.06
	(0.06)	(0.06)
Percent with a College Degree	-1.15	0.95
	(0.91)	(0.81)
Percent Homeowners	0.86	0.18
	(0.64)	(0.61)
Percent Union Members	-0.24	0.14
	(0.09)	(0.08)
Percent White Collar	0.44	-0.88
	(1.24)	(1.11)
Median Income	1.01	-0.22
	(0.75)	(0.54)
Percent African-American*South	0.22	-0.07
	(0.18)	(0.16)
Gini Coefficient	-0.47	
	(3.02)	
Population Size		0.11
		(0.06)
Sullivan Index		2.39
		(2.12)
N	39	39
$R^2$	0.66	0.44

Table 1: OLS regression results showing the relationship between various demographic aggregates and our measure of the mean and variance of state opinion. Here, all demographic indicators have been logged to reduce the effect of outliers (except inequality, though the results are qualitatively similar with a log-restriction on inequality). To aid in interpretation, we multiplied the dependent variable by 10. Results in **bold** can be distinguished from 0 at the  $\alpha = 0.10$  significance level, two-tailed.